Using Machine Learning to Infer Pre-Entry Properties for Asteroid Threat Analysis

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Introduction

Accurately assessing asteroid threats relies on knowledge of the asteroid's pre-entry properties such as size, velocity, and mass. Directly measuring these properties can be infeasible due to the sparsity of events and the accuracy and fidelity of various sensors. Current analysis of an asteroid's pre-entry properties involves modeling the asteroid's entry into the Earth's atmosphere. This process can be time consuming and can require manual adjustment of uncertain modeling specific parameters.

NASA Ames has developed a genetic algorithm that can help automate asteroid modeling using the Fragment-Cloud Model (FCM). The algorithm generates realistic energy deposition curves based on actual energy deposition curves from real, observed asteroids. By using these synthetic, labeled energy deposition curves, we developed a one-dimensional convolutional neural network that can predict an asteroid's pre-entry parameters.

Motivation

- Assessing asteroid treats depends on successful characterization of the asteroid's physical properties
- Current methods requires manual modeling of parameters to match the observed energy deposition curves
- Inferring the pre-entry parameters directly from the energy deposition curve rather than modeling entries to match an observed event would greatly improve risk assessments of new asteroids

Data

- The data generated by FCM produces energy deposition curves from 100 km to 0 km with a resolution of 1km
- The dataset has 2.4 million energy deposition curves
- The data is split 88/2/10 for training, training validation, and testing
- The real asteroids are hand-modeled with FCM to match the documented results from other papers and are used for result validation

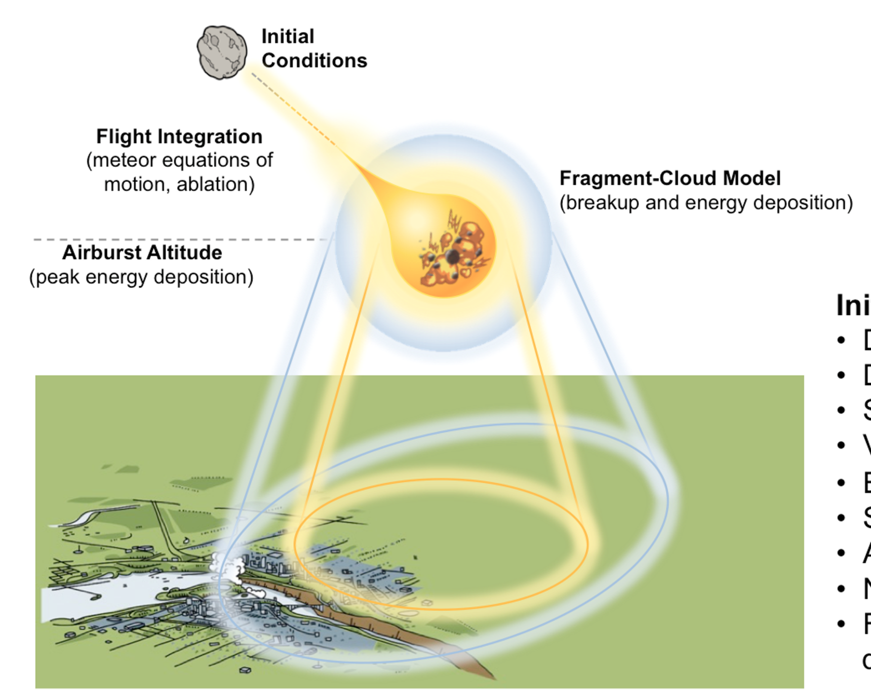
Parameter	Minimum	Maximum	Distribution
Diameter (m)	0.1	50	Uniform
Velocity (km/s)	11	25	Uniform
Entry Angle (°)	10	90	Uniform
Bulk Density (g/cm^3)	1.1	4.0	Uniform
Strength (kPa)	1	15000	Log Uniform

References

- Tárano, Ana María, et al. "Inference of Meteoroid Characteristics Using a Genetic Algorithm." Icarus, vol. 329, 1 Sept. 2019, pp. 270–281., doi:10.1016/j.icarus.2019.04.002.
- Wheeler, Lorien F., et al. "Atmospheric Energy Deposition Modeling and Inference for Varied Meteoroid Structures." Icarus, vol. 315, Nov. 2018, pp. 79–91., doi:10.1016/j.icarus.2018.06.014.

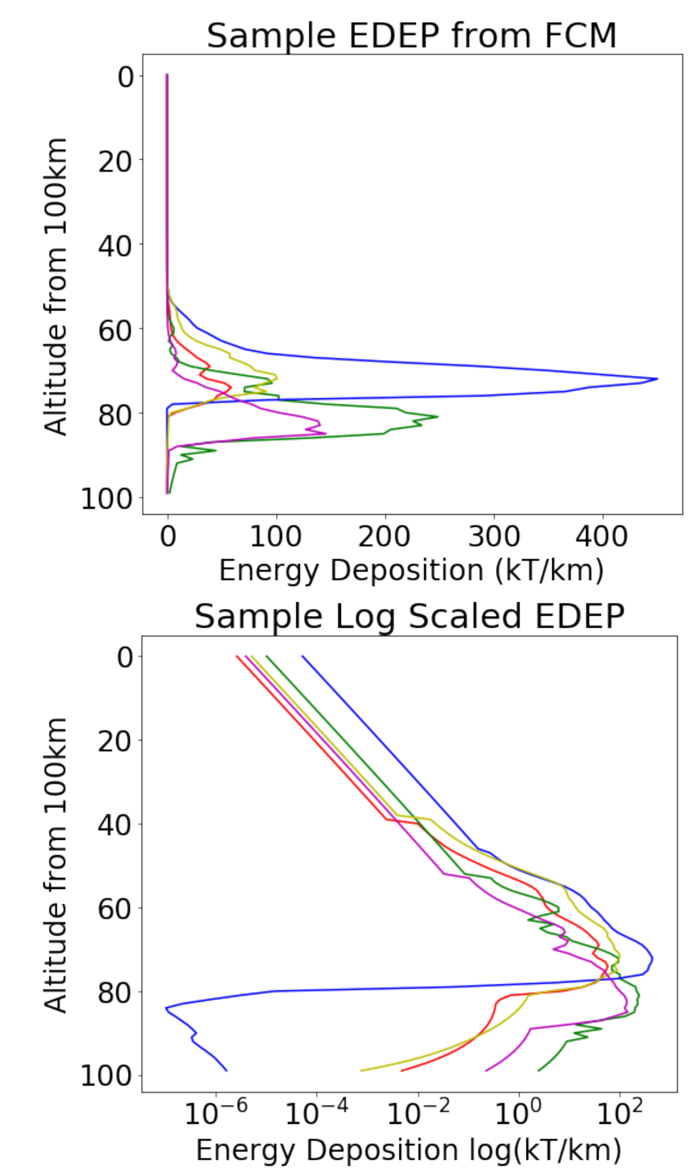
Method

1. Model Asteroid Entries

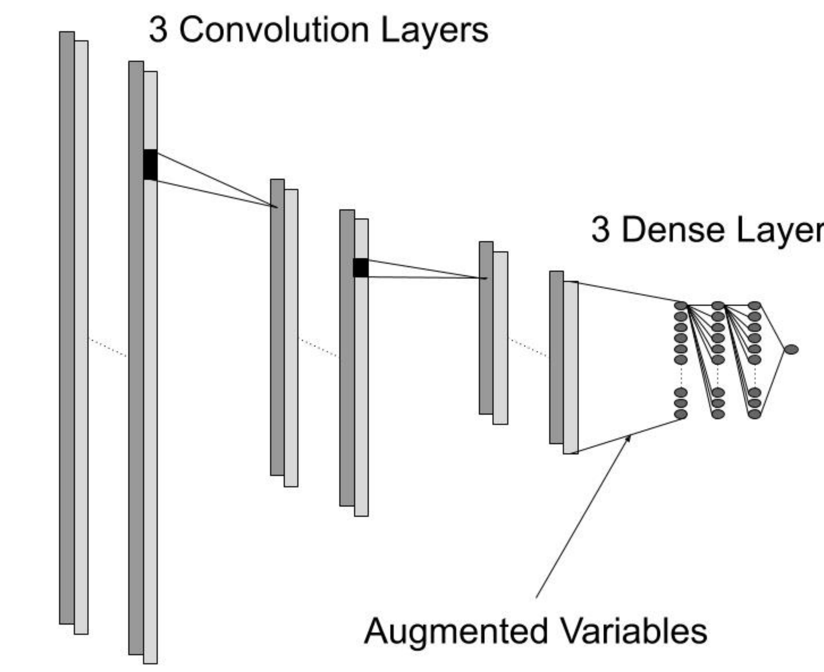


Initial Conditions
- Diameter
- Density
- Strength
- Velocity
- Entry angle
- Strength scaling α
- Ablation coefficient σ
- Number of fragments
- Fragment mass distribution

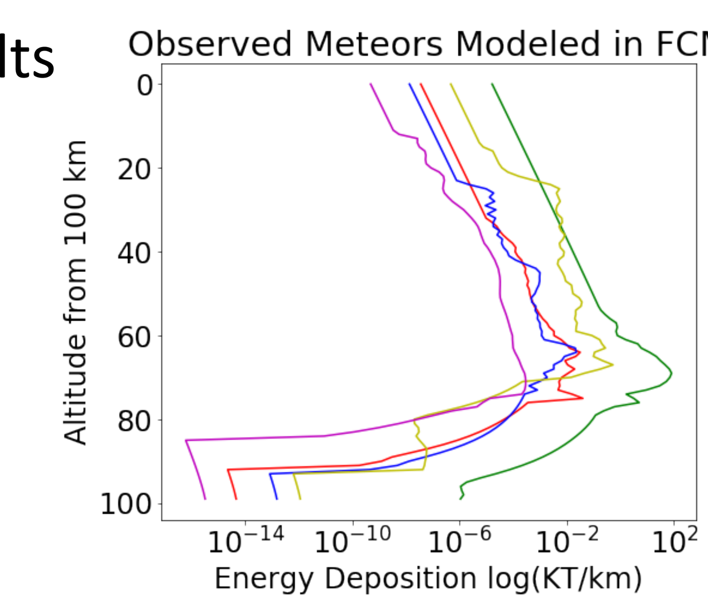
2. Transform Data



3. Train Model



4. Test Results



Model

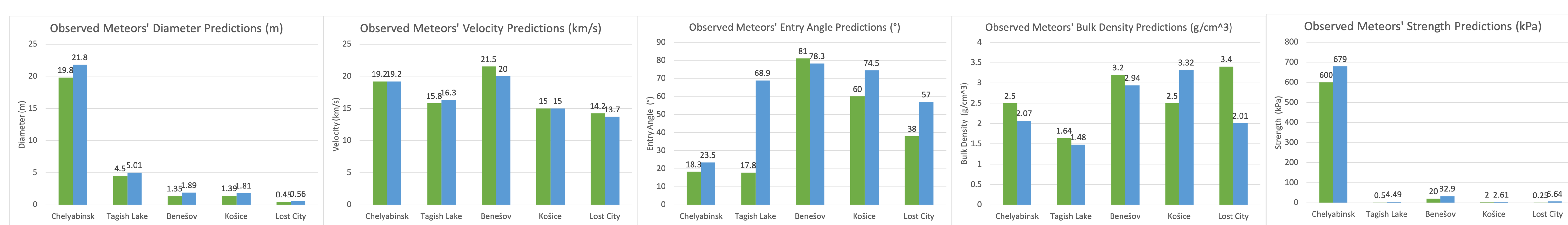
- Input: log scaled energy deposition (EDEP) curve
- Augmented, one-dimensional convolutional neural network
- 3 one-dimensional convolutional layers
- 5 augmented variables: total kinetic energy (KE), mean KE, max KE, and altitude at max KE of the input EDEP curve
- 3 dense layers
- Output: prediction of 1 pre-entry parameter

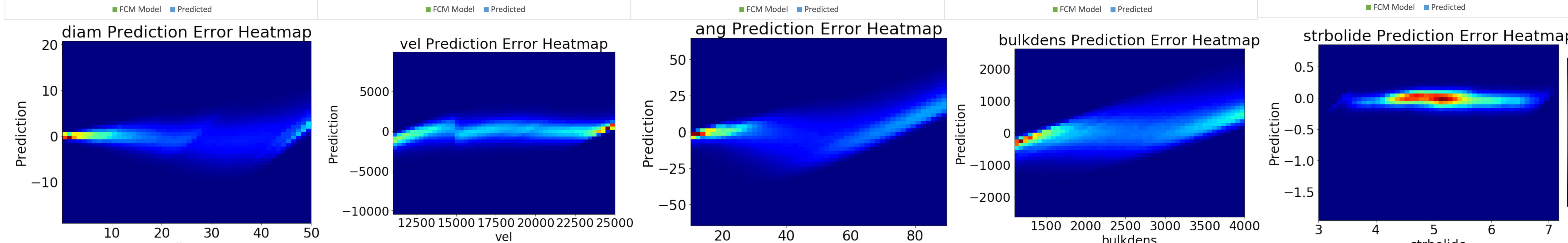
Results

- 5 separate models for each parameter
- Results validated with real modeled asteroids shown in the bar graphs
- Tested with with 10 percent of the synthetic data shown in the error heatmaps and R^2 table

Conclusions

- We can make predictions on real asteroid properties based on a synthetically generated dataset
- We show that our model is quite good at predicting diameter and velocity, and reasonably good at predicting entry angle, bulk density, and strength, for both the real cases as well as the test portion of the dataset
- Extensions to this concept include predicting pre-entry parameters based on light curve data and partial energy deposition curves





R^2 on Test Dataset for each Parameter									
Diameter	0.969	Velocity	0.951	Entry Angle	0.774	Bulk Density	0.628	Strength	0.942